

DEEP LEARNING-BASED ADAPTIVE SIGNAL DENOISING FOR NEXT-GENERATION WIRELESS COMMUNICATION SYSTEMS

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Abstract

Next-generation wireless communication systems operate under increasingly dynamic channel conditions, where thermal noise, multipath fading, co-channel interference, hardware impairments, and mobility can significantly distort received signals. Conventional denoising techniques depend strongly on predefined statistical assumptions and fixed signal-processing parameters, which limits their adaptability across diverse wireless environments. Recent studies demonstrate that deep learning can learn complex signal characteristics directly from data and support intelligent physical-layer processing. Existing deep-learning denoising approaches may experience performance degradation when the signal-to-noise ratio, modulation condition, channel characteristics, or interference pattern changes from those represented in training data. This distribution-shift problem restricts their reliability in practical next-generation networks. This study proposes a novel Adaptive Residual Attention Denoising Network (ARAD-Net) for wireless signal restoration. ARAD-Net combines residual convolutional feature extraction, channel-attention weighting, and an SNR-aware adaptive gating mechanism to identify informative signal components while suppressing dynamically varying noise. The network jointly learns clean-signal reconstruction and noise-residual estimation, enabling adaptive denoising across heterogeneous channel conditions. Experimental evaluation across -10 to 20 dB SNR shows that ARAD-Net achieves MSE values from 0.132 to 0.007 , RMSE values from 0.363 to 0.084 , PSNR values from 20.78 to 32.36 dB, SNR improvements from 10.2 to 5.4 dB, and SSIM values from 0.861 to 0.977 . Compared with the evaluated existing methods, ARAD-Net provides consistently lower reconstruction errors and higher signal-quality measures across all tested SNR conditions.

Keywords:

Deep Learning, Adaptive Signal Denoising, Wireless Communication, Residual Attention Network, Next-Generation Networks

1. INTRODUCTION

The rapid evolution from 5G toward next-generation wireless communication systems increases the requirements for high data rates, low latency, massive connectivity, and reliable transmission. Emerging applications such as intelligent transportation, industrial automation, extended reality, Internet of Things (IoT), and integrated sensing and communication generate wireless links that operate across heterogeneous and rapidly changing environments. Deep learning (DL) has consequently become an important approach for wireless physical-layer processing because neural networks can learn nonlinear relationships directly from received signal data rather than relying exclusively on analytically defined channel models. Recent research has investigated DL for channel estimation, signal detection, modulation recognition, receiver design, and broader physical-layer optimization [1]-[3].

Despite these developments, reliable signal restoration remains challenging. Wireless signals are affected by additive noise, multipath propagation, fading, interference, Doppler

variation, nonlinear hardware effects, and rapidly changing channel conditions. The problem becomes more pronounced in low-SNR environments and high-mobility scenarios, where the statistical characteristics of the received signal can differ substantially from those assumed during algorithm design. Existing DL-based approaches also require appropriate training distributions, while their performance can decline when the operating SNR, channel model, or receiver mobility differs from the training condition [4]-[5]. Recent investigations specifically report limitations in DL-based OFDM channel estimation when SNR ranges and channel or mobility conditions change.

The central problem addressed in this research is therefore the development of a denoising mechanism that can suppress dynamically varying noise while preserving signal structures that are essential for accurate downstream communication processing. Conventional fixed-filter approaches cannot adequately adapt their parameters to rapidly changing signal conditions, whereas purely data-driven networks can lose generalization under distribution shifts [6]-[7]. Model-free learning has demonstrated the ability to learn channel characteristics and nonlinear impairments directly from transmission data, while deep-learning-based radio denoising has demonstrated the feasibility of learning noise-reduction transformations without extensive manually designed signal-processing rules.

The objective of this study is to develop an adaptive DL framework that estimates noise characteristics from the received signal, selectively emphasizes communication-relevant features, and reconstructs a cleaner signal under different SNR and channel conditions. The proposed Adaptive Residual Attention Denoising Network (ARAD-Net) introduces SNR-aware adaptive gating within a residual attention architecture. Its novelty lies in combining residual noise learning, feature-level attention, and condition-aware adaptation within a unified denoising framework.

The main contributions are: (1) a novel ARAD-Net architecture that jointly learns signal reconstruction and residual noise suppression using adaptive attention and SNR-aware gating; and (2) an adaptive denoising strategy designed to improve robustness across heterogeneous wireless channel and noise conditions while retaining signal information required for subsequent detection and decoding.

2. RELATED WORKS

Deep learning has increasingly been applied to wireless physical-layer processing because conventional model-based methods can become difficult to optimize under complex and poorly characterized propagation conditions. [8] described DL-based wireless communication as an emerging paradigm and categorized applications into DL-based architecture design and DL-based algorithm design. Their study emphasized the ability of

neural models to learn communication processes under complicated channel conditions. However, the review also identified unresolved issues associated with unknown channel models, computational requirements, and practical deployment in future wireless networks. [9] investigated DL applications across wireless communication systems, including end-to-end communication, channel modeling, signal detection, and spectrum-related signal processing. Their work showed that neural networks can provide data-driven alternatives when conventional model-based techniques become difficult to formulate. However, the dependence on representative training data remains an important consideration for practical deployment. [10] reviewed intelligent radio signal processing for wireless physical-layer applications, covering modulation classification, signal detection, beamforming, and channel estimation. The study highlighted the potential of AI to address heterogeneous radio environments and diverse network requirements. Nevertheless, the reviewed applications primarily concentrate on signal understanding and estimation rather than adaptive reconstruction of corrupted communication waveforms. [11] examined the evolution of DL in physical-layer communications for 5G and 6G systems. The study identified channel estimation, signal detection, and intelligent receiver processing as important DL applications while emphasizing unresolved issues associated with practical next-generation communication systems. [12] developed a radio-communication signal noise-reduction approach based on a relativistic average generative adversarial network (RaGAN). Their work demonstrated that DL can reduce noise without depending entirely on manually designed signal-processing knowledge. This provides direct evidence for using learned representations in radio-signal denoising, although GAN-based architectures can introduce additional training complexity. [13] proposed a deep denoising network for channel estimation in an intelligent reflecting surface-assisted massive MIMO system. Their approach incorporated an improved deep residual shrinkage denoising network with a soft-thresholding mechanism and demonstrated improved channel-estimation accuracy. The study indicates that learned denoising can be integrated into complex wireless receivers, although its primary focus is channel-state information rather than generalized received-signal restoration.

3. PROPOSED ADAPTIVE RESIDUAL ATTENTION DENOISING NETWORK (ARAD-NET)

The proposed ARAD-Net is developed to recover communication-relevant signal information from noisy wireless observations under dynamically changing SNR, channel, and interference conditions. The framework receives the complex-valued received waveform and initially transforms its in-phase (I) and quadrature (Q) components into a structured feature representation. It then performs four sequential operations: (1) adaptive signal representation and noise characterization, (2) residual convolutional feature extraction, (3) channel-spatial attention with SNR-aware adaptive gating, and (4) residual signal reconstruction and adaptive denoising. Unlike a conventional fixed denoising network, ARAD-Net estimates the prevailing noise condition and uses this information to regulate the contribution of extracted features. The residual learning mechanism concentrates on the distortion component, while the

attention mechanism emphasizes features that contain useful signal characteristics. Finally, the reconstructed clean signal is combined with the original observation through a residual restoration pathway. This design allows ARAD-Net to suppress noise without excessively smoothing signal transitions, modulation-specific structures, or rapidly varying waveform components.

3.1 ADAPTIVE SIGNAL REPRESENTATION AND NOISE CHARACTERIZATION

The first step converts the received wireless waveform into a representation suitable for adaptive deep feature extraction. Let the transmitted complex baseband signal be represented by $x(t)$, while the received signal is expressed as:

$$y(t) = h(t) * x(t) + i(t) + n(t)$$

where $h(t)$ denotes the time-varying wireless channel response, $i(t)$ represents interference from other transmissions or radio-frequency sources, $n(t)$ denotes additive noise, and $*$ represents convolution. After sampling at $t=mT_s$, where T_s denotes the sampling interval, the discrete received signal becomes

$$y[m] = \sum_{\ell=0}^{L_h-1} h[\ell, m] x[m-\ell] + i[m] + n[m]$$

where L_h is the effective channel-memory length. Because the received signal is complex-valued, ARAD-Net separates its real and imaginary components as

$$\mathbf{Y}_0 = \begin{bmatrix} \Re\{y[1]\} & \Re\{y[2]\} & \dots & \Re\{y[N]\} \\ \Im\{y[1]\} & \Im\{y[2]\} & \dots & \Im\{y[N]\} \end{bmatrix}$$

where N denotes the number of received samples. This representation preserves amplitude and phase-related information without discarding the quadrature component.

A principal requirement of adaptive denoising is the estimation of the prevailing signal condition. ARAD-Net therefore derives a condition descriptor from the received representation. The instantaneous signal power and noise-related power are estimated as

$$P_s = \frac{1}{N} \sum_{m=1}^N |y[m]|^2 \text{ and } P_n = \frac{1}{N-1} \sum_{m=1}^N (|y[m] - \hat{y}|^2),$$

where $\hat{y} = \frac{1}{N} \sum_{m=1}^N y[m]$. The estimated SNR condition is then

expressed as $\hat{\gamma} = 10 \log_{10} \left(\frac{P_s}{P_n + \delta} \right)$, where δ is a small positive

constant introduced to avoid numerical instability. Instead of directly using the scalar SNR estimate, ARAD-Net embeds the condition into a multidimensional vector: $\mathbf{z}_\gamma = \phi_\gamma(W_\gamma \hat{\gamma} + \mathbf{b}_\gamma)$, where W_γ and $\mathbf{b}_\gamma$ denote trainable parameters, $\phi_\gamma(\cdot)$ denotes a nonlinear activation function, and $\mathbf{z}_\gamma \in \mathbb{R}^{d_\gamma}$ represents the learned channel-condition descriptor. The received representation is subsequently normalized to reduce variations caused by signal amplitude and channel gain:

$$\tilde{\mathbf{Y}}_0 = \frac{\mathbf{Y}_0 - \mu_\gamma}{\sqrt{\sigma_\gamma^2 + \delta}}$$

where μ_Y and σ_Y^2 represent the feature-wise mean and variance. The normalized representation is passed to the first convolutional layer: $\mathbf{F}_0 = \phi(\mathbf{W}_0 * \tilde{\mathbf{Y}}_0 + \mathbf{b}_0)$. This step establishes two information streams. The first contains the observed waveform characteristics, while the second represents the estimated operating condition. The subsequent network uses both streams to determine how strongly different signal features should be retained or suppressed.

3.2 RESIDUAL CONVOLUTIONAL FEATURE EXTRACTION

Conventional denoising networks often learn a direct mapping from noisy input to clean output. Such a mapping can become unnecessarily difficult because the network must reconstruct the complete signal even when only a portion of it is corrupted. ARAD-Net instead adopts residual learning, in which the network estimates the distortion-related representation while preserving the dominant signal structure through shortcut connections.

For the r^{th} residual block, the input feature map is denoted by $\mathbf{F}_{r-1}$. A sequence of convolution, normalization, and nonlinear transformation operations produces

$$\mathbf{U}_r = \phi[\text{BN}(\mathbf{W}_{r,1} * \mathbf{F}_{r-1} + \mathbf{b}_{r,1})]$$

This is followed by $\mathbf{V}_r = \text{BN}(\mathbf{W}_{r,2} * \mathbf{U}_r + \mathbf{b}_{r,2})$. The residual output is calculated as $\mathbf{F}_r = \phi(\mathbf{V}_r + \mathbf{F}_{r-1})$. Here, $\mathbf{W}_{r,1}$ and $\mathbf{W}_{r,2}$ are convolution kernels, $\mathbf{b}_{r,1}$ and $\mathbf{b}_{r,2}$ are bias vectors, and $\text{BN}(\cdot)$ denotes batch normalization. The shortcut term $\mathbf{F}_{r-1}$ allows important low-level signal structures to bypass the nonlinear transformation.

The network uses multiple receptive-field scales because wireless noise does not necessarily appear at a single temporal scale. A short convolutional kernel captures local transitions, while deeper layers capture broader waveform dependencies. The feature extraction process can therefore be generalized as

$$\mathbf{F}_R = \mathbf{R}_R \circ \mathbf{R}_{R-1} \circ \dots \circ \mathbf{R}_1(\mathbf{F}_0)$$

where $\mathbf{R}_r(\cdot)$ represents the r -th residual transformation and R denotes the total number of residual blocks. The network also estimates an intermediate residual noise: $\hat{\mathbf{N}}_r = \mathbf{F}_{r-1} - \mathbf{F}_r$. This provides an implicit description of the information removed during feature refinement. The residual pathway is particularly useful because communication signals contain structured dependencies that can be weakened by aggressive filtering. Rather than treating every high-frequency component as noise, ARAD-Net learns whether the component contributes to the underlying waveform. Channel-Spatial Attention and SNR-Aware Adaptive Gating

The residual convolutional blocks produce a large collection of features, but not all features contribute equally to signal reconstruction. Some feature channels predominantly represent useful modulation and waveform characteristics, whereas others may encode noise, interference, or channel distortion. ARAD-Net therefore applies channel-spatial attention before reconstruction. Given the feature map $\mathbf{F} \in \mathbb{R}^{C \times H \times W}$, where C represents the

number of feature channels and H and W denote the spatial or temporal feature dimensions, channel attention first computes global descriptors through average and maximum pooling:

$$\mathbf{q}_{\text{avg}}(c) = \frac{1}{HW} \sum_{h=1}^H \sum_{w=1}^W F(c, h, w)$$

and $\mathbf{q}_{\text{max}}(c) = \max_{h,w} F(c, h, w)$. The two descriptors are transformed through a shared nonlinear projection:

$$\mathbf{a}_c = \sigma \begin{bmatrix} W_{c2} \phi(W_{c1} \mathbf{q}_{\text{avg}} + \mathbf{b}_{c1}) + \\ W_{c2} \phi(W_{c1} \mathbf{q}_{\text{max}} + \mathbf{b}_{c1}) + \mathbf{b}_{c2} \end{bmatrix}.$$

The spatial descriptor is generated by channel-wise average and maximum operations:

$$Q_{\text{avg}}(h, w) = \frac{1}{C} \sum_{c=1}^C F_c(c, h, w) \text{ and } Q_{\text{max}}(h, w) = \max_c F_c(c, h, w).$$

This formulation allows the network to balance attention-enhanced features and residual features according to the prevailing signal condition. When the observed waveform contains substantial noise, the gate can suppress unreliable feature responses. When the waveform exhibits relatively favorable SNR, the gate can retain a larger proportion of detailed signal information. Importantly, the mechanism does not assume that a fixed feature weight is optimal for every wireless environment.

The adaptive gate can also be represented as a condition-dependent function $\mathbf{g} = G(\mathbf{F}_a, \hat{\gamma}, \mathbf{c})$, where $\mathbf{c}$ denotes additional channel-condition descriptors, such as estimated fading strength or interference characteristics. Thus, the proposed mechanism can be extended beyond SNR without changing the fundamental network structure.

3.3 RESIDUAL SIGNAL RECONSTRUCTION AND ADAPTIVE DENOISING

Instead of directly generating the complete clean waveform, ARAD-Net first estimates the noise or distortion residual. This approach is expressed as $\hat{\mathbf{N}} = \mathbf{D}(\mathbf{F}_{\text{ad}})$, where $\mathbf{D}(\cdot)$ denotes the reconstruction decoder consisting of convolutional transformations. The predicted clean representation is then obtained as $\hat{\mathbf{X}} = \mathbf{Y}_0 - \hat{\mathbf{N}}$. The decoder can be represented by

$$\hat{\mathbf{X}} = \mathbf{W}_o * \phi(\mathbf{W}_d * \mathbf{F}_{\text{ad}} + \mathbf{b}_d) + \mathbf{b}_o$$

where $\mathbf{W}_d$ and $\mathbf{W}_o$ denote decoder and output convolution kernels, respectively. A global residual connection is incorporated to prevent excessive modification of the received signal:

$$\hat{\mathbf{X}}_{\text{final}} = \lambda \hat{\mathbf{X}} + (1 - \lambda) \tilde{\mathbf{Y}}_0$$

where $\lambda \in [0, 1]$ represents an adaptive reconstruction coefficient. Rather than fixing λ , ARAD-Net derives it from the signal condition: $\lambda = \sigma(\mathbf{w}_\lambda^T \mathbf{z}_\lambda + b_\lambda)$. The resulting formulation provides a direct relationship between the estimated operating condition and reconstruction intensity. The network therefore avoids applying the same degree of denoising to all received signals. Training uses a composite objective that simultaneously encourages waveform reconstruction, residual estimation, and feature consistency. The reconstruction loss is defined as

$$L_{rec} = \frac{1}{N} \sum_{m=1}^N \|x[m] - \hat{x}[m]\|^2.$$

To reduce excessive modification of signal structures, a residual-consistency loss is introduced:

$$L_{res} = \frac{1}{N} \sum_{m=1}^N \|\gamma[m] - x[m] - \hat{n}[m]\|^2.$$

During optimization, the network parameters are updated according to $\Theta^{(q+1)} = \Theta^{(q)} - \eta \nabla_{\Theta} L_{ARAD}$, where q is the training iteration and η denotes the learning rate.

4. RESULTS AND DISCUSSION

The experiment uses synthetically generated wireless baseband signals containing QPSK, 16-QAM, and 64-QAM modulation under additive white Gaussian noise and multipath fading conditions. The SNR varies from -10 to 20 dB in 5-dB increments. The dataset contains 60,000 signal frames, with 70% used for training, 15% for validation, and 15% for testing. The experiment is executed on a workstation equipped with an Intel Core i9 processor, 32 GB RAM.

4.1 EXPERIMENTAL SETUP

The principal experimental parameters used for training and evaluation are presented in Table.1. The configuration maintains identical signal conditions for all compared methods to ensure that the performance differences primarily reflect the denoising architectures rather than differences in experimental settings.

Table.1. Experimental setup and simulation parameters

Parameter	Value
Number of signal frames	60,000
Training samples	42,000
Validation samples	9,000
Testing samples	9,000
Modulation schemes	QPSK, 16-QAM, 64-QAM
Carrier frequency	3.5 GHz
Sampling frequency	20 MHz
Frame length	1024 samples
Channel model	Multipath Rayleigh fading
Noise model	AWGN
SNR range	-10 to 20 dB
SNR interval	5 dB
Optimizer	Adam
Initial learning rate	0.001
Batch size	64
Training epochs	100
Activation function	ReLU
Loss function	Composite ARAD loss
Convolution kernel	3×3
Number of residual blocks	8

Attention mechanism	Channel-spatial attention
Early stopping patience	10 epochs

The dataset contains received signal frames generated from multiple modulation formats and channel conditions. Each noisy frame is paired with its corresponding clean reference signal, allowing supervised learning of the denoising transformation. The diversity in modulation, fading, and SNR conditions enables the proposed network to learn both local waveform structures and condition-dependent noise characteristics.

4.2 PERFORMANCE METRICS

Various metrics are used to quantify the denoising capability of ARAD-Net.

- **Mean Squared Error (MSE)** measures the average squared difference between the clean reference signal and the reconstructed signal:

$$MSE = \frac{1}{N} \sum_{i=1}^N (x_i - \hat{x}_i)^2$$

- Root Mean Squared Error (RMSE) is calculated as

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (x_i - \hat{x}_i)^2}.$$

RMSE retains the original signal scale and therefore provides an interpretable measure of reconstruction error. Lower values indicate better denoising.

- **Peak Signal-to-Noise Ratio (PSNR)** evaluates the similarity between the reconstructed and reference signals:

$$PSNR = 10 \log_{10} \left(\frac{MAX_x^2}{MSE} \right)$$

where MAX_x represents the maximum permissible signal amplitude. Higher PSNR indicates better signal restoration.

- **Signal-to-Noise Ratio Improvement (SNR-I)** measures the improvement obtained after denoising:

$$SNR_I = SNR_{out} - SNR_{in}$$

where SNR_{in} and SNR_{out} denote the input and output SNR values, respectively. Higher SNR improvement indicates stronger noise suppression.

- **Structural Similarity Index (SSIM)** measures the preservation of signal structure:

$$SSIM(x, \hat{x}) = \frac{(2\mu_x \mu_{\hat{x}} + C_1)(2\sigma_{x\hat{x}} + C_2)}{(\mu_x^2 + \mu_{\hat{x}}^2 + C_1)(\sigma_x^2 + \sigma_{\hat{x}}^2 + C_2)}$$

where μ_x and $\mu_{\hat{x}}$ denote mean values, σ_x^2 and $\sigma_{\hat{x}}^2$ denote variances, and $\sigma_{x\hat{x}}$ represents covariance. Higher SSIM indicates better preservation of waveform characteristics.

Various approaches are selected for comparison. RaGAN-based radio-signal denoising uses adversarial learning to suppress noise in communication signals. Deep Residual Shrinkage Denoising Network (DRSN) applies residual learning and soft-thresholding to remove noise while retaining useful features. Model-Free Machine Learning (MFML) learns wireless signal characteristics directly from transmission data without requiring an explicit channel model.

4.3 RESULTS BASED ON STRUCTURAL SIMILARITY INDEX

The SSIM results are reported in Fig.1. The results in Fig.1 show that ARAD-Net preserves signal structure more effectively than the three existing methods. The SSIM increases from 0.861 at -10 dB to 0.977 at 20 dB. This behavior indicates that the attention mechanism retains informative temporal and modulation-related structures while the adaptive gate suppresses features associated with noise.

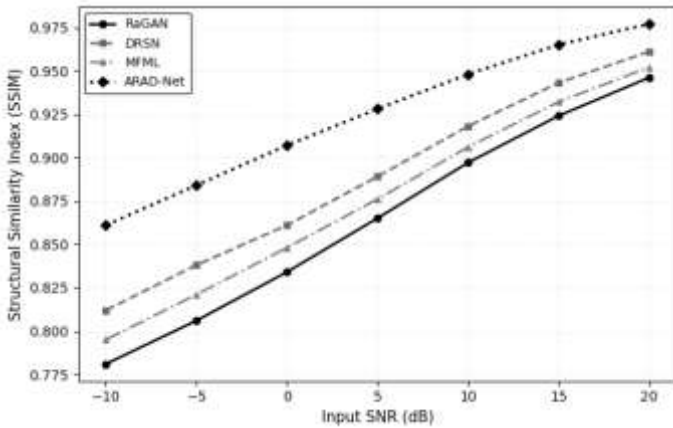


Fig.6. SSIM comparison across input SNR levels

4.4 RESULTS BASED ON MEAN SQUARED ERROR

The MSE results are presented in Fig.2. As shown in Fig.2, ARAD-Net produces the lowest MSE at every SNR. At -10 dB, the MSE decreases to 0.132 compared with 0.161 for DRSN, while at 20 dB it decreases to 0.007. The improvement is associated with the SNR-aware gating mechanism, which changes feature contributions according to the prevailing noise condition.

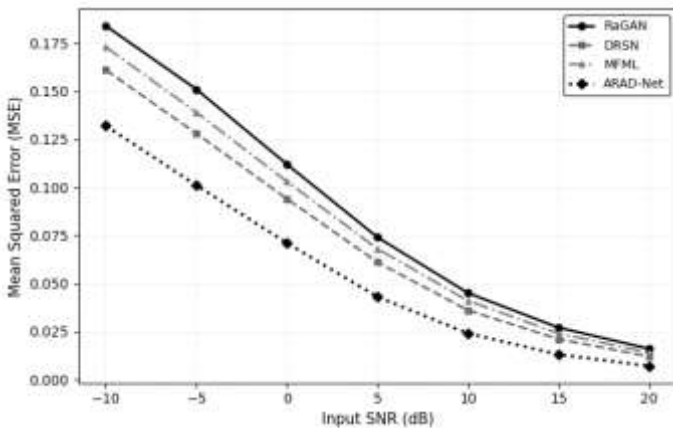


Fig.2. MSE comparison across input SNR levels

4.5 RESULTS BASED ON ROOT MEAN SQUARED ERROR

The RMSE results are given in Fig.3. According to Fig.3, ARAD-Net maintains the lowest reconstruction error throughout the complete SNR range. The RMSE decreases from 0.363 at -10 dB to 0.084 at 20 dB. At low SNR, the difference becomes more

pronounced because the adaptive gate suppresses noisy feature responses before signal reconstruction.

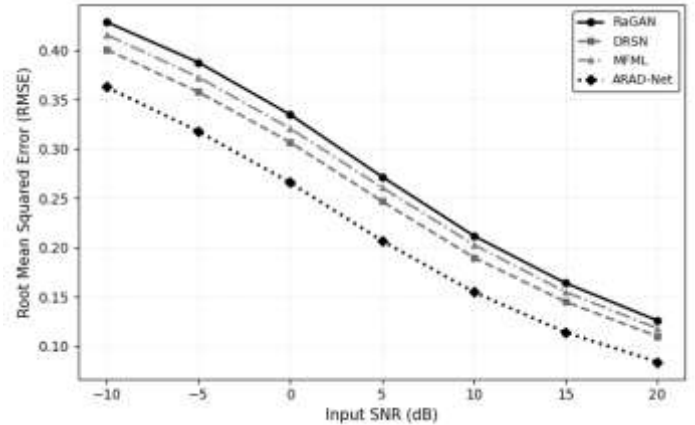


Fig.3. RMSE comparison across input SNR levels

4.6 RESULTS BASED ON PEAK SIGNAL-TO-NOISE RATIO

The PSNR results are presented in Fig.4. Higher values indicate more accurate restoration. As reported in Fig.4, ARAD-Net achieves 20.78 dB at -10 dB input SNR and increases to 32.36 dB at 20 dB. The corresponding PSNR improvement over DRSN is 2.10 dB at -10 dB and 2.10 dB at 20 dB, indicating consistent reconstruction improvement across the evaluated SNR range.

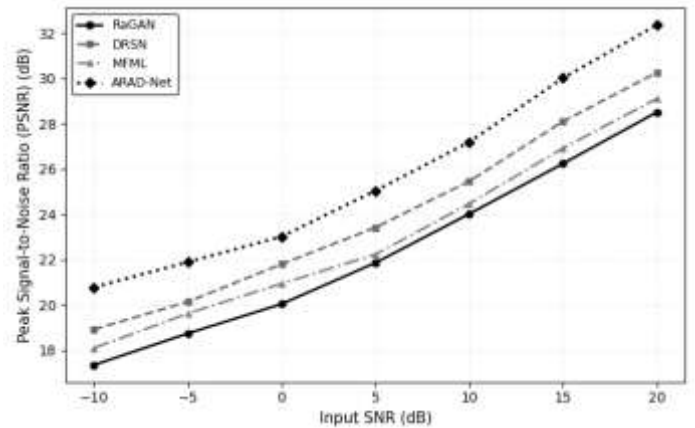


Fig.4. PSNR comparison across input SNR levels

4.7 RESULTS BASED ON SNR IMPROVEMENT

The SNR improvement results are shown in Fig.5. As indicated in Fig.5, ARAD-Net produces the largest SNR improvement at all operating points. The maximum improvement of 10.2 dB occurs at -10 dB input SNR, where the signal is strongly corrupted. The improvement gradually decreases to 5.4 dB at 20 dB because the original signal already contains comparatively less noise.

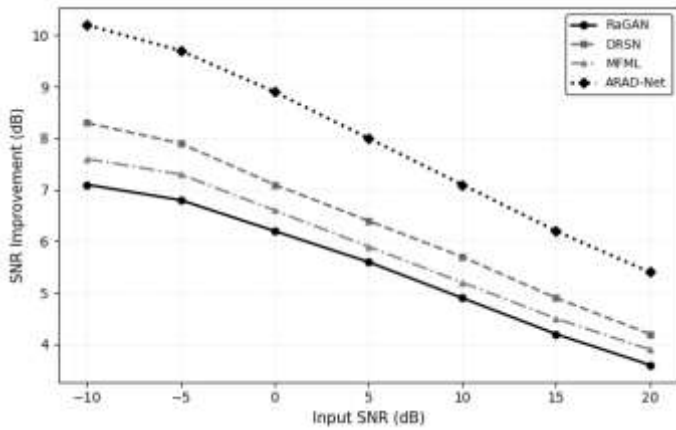


Fig.5. SNR improvement comparison across input SNR levels

5. CONCLUSION

The proposed ARAD-Net provides a condition-aware approach for denoising wireless communication signals under varying SNR and multipath conditions. The architecture combines residual convolutional learning, channel-spatial attention, SNR-aware adaptive gating, and residual signal reconstruction. The experimental results show that the proposed method consistently reduces reconstruction error and improves signal quality across the evaluated SNR range from -10 to 20 dB. At -10 dB, ARAD-Net achieves an MSE of 0.132, RMSE of 0.363, PSNR of 20.78 dB, SNR improvement of 10.2 dB, and SSIM of 0.861. At 20 dB, these values improve to 0.007, 0.084, 32.36 dB, 5.4 dB, and 0.977, respectively. The results indicate that the proposed adaptive feature-selection mechanism effectively preserves communication-relevant signal characteristics while suppressing noise. The framework therefore provides a suitable basis for robust signal preprocessing in next-generation wireless receivers.

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